Jurnal
Teknologi

Full Paper

An Exponentially Weighted Moving Average Method with Designed Input Data Assignments for Forecasting Lime Prices in Thailand

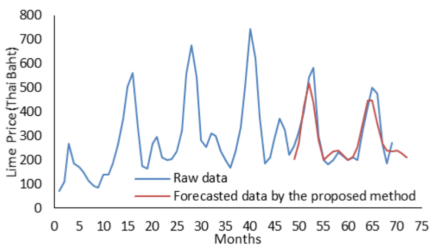
Article history
Received
28 November 2016
Received in revised form
15 July 2017
Accepted
10 August 2017

Thitima Booranawong[a], Apidet Booranawong[b*]

[a]Faculty of Management Sciences, Nakhon Si Thammarat Rajabhat University, Nakhon Si Thammarat 80280, Thailand
[b]Faculty of Engineering, Thaksin University, Phatthalung Campus, Phatthalung 93210, Thailand

*Corresponding author
apidet@tsu.ac.th

Graphical abstract



Abstract

In this paper, the Exponentially Weighted Moving Average (EWMA) method with designed input data assignments (i.e. the proposed method) is presented to forecast lime prices in Thailand during January 2016 to December 2016. The lime prices from January 2011 to December 2015 as the input data are gathered from the website's database of Simummuang market, which is one of the big markets in Thailand. The novelty of our paper is that although the performance of the EWMA method significantly decreases when applying to forecast data which show trend and seasonality behaviors and the EWMA method is used for short-range forecasting (i.e. usually one month into the future), the proposed method can properly handle such mentioned problems. For this purpose, to forecast lime prices, five different input data are intently defined before assigned to the EWMA method: a) the monthly data of the year 2015 (i.e. the recent year data), b) the average monthly data of the year 2011 to 2015, c) the median of the monthly data of the year 2011 to 2015, d) the monthly data of the year 2011 to 2015 after applying the linear weighting factor, where the higher weight value is applied to the recent data, and e) the average monthly data of the year 2011 to 2015 after applying the exponential weighting factor, where the higher weight is also applied to the recent data. These designed input data are used as agents of the raw data. Our study reveals that using the input data b) with the EWMA method to forecast lime prices during January 2016 to September 2016 gives the smallest forecasting error measured by the Mean Absolute Percentage Error (MAPE). Forecasted lime prices of October 2016 to December 2016 are also provided. Additionally, we demonstrate that the proposed method works well compared with the Double Exponentially Weighted Moving Average (DEWMA), the Multiplicative Holt-Winters (MHW), and the Additive Holt-Winters (AHW) methods, which are suitably used for forecasting data with the trend and the seasonality.

Keywords: Forecasting, exponentially weighted moving average, double exponentially weighted moving average, Holt-Winters, lime prices

1.0 INTRODUCTION

Thai lime is one of the essential economic plants in Thailand. Because the lime has its own sour taste, it can be integrated as part of many Thai foods and beverages. Additionally, the lime price is quite high especially during the summer season in Thailand that it is very attractive for Thai agriculturists to sell the lime for gaining higher profits. Consequently, knowing the selling price or its trend before selling is very useful for Thai agriculturists to appropriately plan their planting and harvesting schedules. We note that, in general, there are a small number of limes grown and harvested during the summer time due to the weather condition in Thailand. Thus, to develop an agricultural technology to support the lime production is required.

In this work, the well-known EWMA method [1-3] as a time series based method is used to forecast lime prices in Thailand of the year 2016. The lime prices from January 2011 to December 2015 are gathered from the website's database of Simummuang market, and they are used as the input data for the EWMA method. Although to forecast data by the EWMA method is not new as presented in the research literature, many research works applied this method to their works due to its simplicity, low computational complexity, and efficiency [4, 5, 13-15]. However, as mentioned before, the performance of the EWMA method decreases when data to be forecasted show trend and seasonality behaviors [5, 6]. To solve this problem, the DEWMA method, and the Holt-Winters (HW) methods are introduced and used instead, where the DEWMA method is appropriately used when the data shows the trend, and the HW methods are often used when the data shows both the trend and the seasonality [6, 8, 9].

Because the EWMA method cannot appropriately apply for the data which show trend and seasonality behaviors, in this work the EWMA method with designed input data assignments is presented to handle such a problem. The main design concept of our proposed method is that the raw input data are redesigned before using as actual inputs for the EWMA method. The designed input data are the monthly data of the recent year, the average monthly data of the past years, the median of the monthly data of the past years, the monthly data of the past years after applying the linear weighting factor, and the average monthly data of the past years after applying the exponential weighting factor. These designed input data are used as agents of the raw data. Our test results indicate that using the average monthly data of the year 2011 to 2015 as the input data for the EWMA method (with an optimal weighting factor) provides the smallest MAPE error on forecasting the lime prices in Thailand. Also, the proposed method shows good results compared with the DEWMA, the MHW, and the AHW methods.

This paper is organized as follows. Section 2 explains materials and methods including details of the input data, test cases and input data assignments, the EWMA method, the DEWMA and the HW methods, and the performance index. Section 3 describes results and discussion. Finally, we conclude this paper and explain limitations of the proposed method in Section 4.

2.0 METHODOLOGY

2.1 Input Data

The lime prices from January 2011 to September 2016 are gathered from the website of Simummuang market [11], which is one of the big markets located in Pathum Thani, Thailand. The monthly lime prices are shown in Table 1.

Table 1 The monthly lime prices in Thai Baht unit from January 2011 to September 2016 (i.e. raw data)

	Monthly lime prices of the years 2011 to 2016					
Months	2011	2012	2013	2014	2015	2016
1	71.77	265.16	235.67	236.13	261.94	210.00
2	110.00	369.66	320.00	337.14	314.29	200.00
3	269.35	502.90	558.06	505.00	398.21	320.00
4	184.83	561.33	676.67	745.00	544.83	421.67
5	169.68	336.45	542.19	622.41	581.10	500.00
6	149.33	173.00	281.67	373.33	298.33	473.33
7	113.55	163.23	251.61	187.10	200.00	264.52
8	92.90	267.74	309.35	211.29	182.26	183.87
9	84.67	295.00	300.00	289.33	200.00	270.59
10	140.00	209.03	235.45	370.97	232.26	-
11	140.00	200.00	196.00	326.33	218.33	-
12	187.00	204.84	169.03	222.58	200.00	-

2.2 Test Cases and Designed Input Data Assignments

To forecast monthly lime prices, we provide two test cases. In the first case, we use the monthly data of the year 2011 to 2014 as the input data for the EWMA method to forecast monthly lime prices of the year 2015. In the second case, we use the monthly data of the year 2011 to 2015 as the input data to forecast monthly lime prices of the year 2016.

Table 2 Notation of the monthly lime prices from January 2011 to September 2016

	Notation of the monthly lime prices of the years 2011 to 2016					
Months	2011	2012	2013	2014	2015	2016
1	A_1	B_1	C_1	D_1	E_1	F_1
2	A_2	B_2	C_2	D_2	E_2	F_2
3	A_3	B_3	C_3	D_3	E_3	F_3
4	A_4	B_4	C_4	D_4	E_4	F_4
5	A_5	B_5	C_5	D_5	E_5	F_5
6	A_6	B_6	C_6	D_6	E_6	F_6
7	A_7	B_7	C_7	D_7	E_7	F_7
8	A_8	B_8	C_8	D_8	E_8	F_8
9	A_9	B_9	C_9	D_9	E_9	F_9
10	A_{10}	B_{10}	C_{10}	D_{10}	E_{10}	-
11	A_{11}	B_{11}	C_{11}	D_{11}	E_{11}	-
12	A_{12}	B_{12}	C_{12}	D_{12}	E_{12}	-

In the first case, five designed input data are: a) $Input_1$; the monthly data of the year 2014 as shown in (1), b) $Input_2$; the average monthly data of the year 2011 to 2014 as shown in (2), c) $Input_3$, the median of the monthly data of the year 2011 to 2014 as shown in (3), d) $Input_4$, the monthly data of the year 2011 to 2014 after applying the linear weighting factor as shown in (4), and e) $Input_5$, the average monthly data of the year 2011 to 2014 after applying the exponential weighting factor as also shown in (4). Notation of the monthly lime prices from January 2011 to September 2016 is presented in Table 2.

$$Input_1 = [D_1, D_2, \ldots, D_{12}] \quad (1)$$

$$Input_2 = \begin{bmatrix} Mean(A_1, B_1, C_1, D_1), Mean(A_2, B_2, C_2, D_2), \ldots \\ , Mean(A_{12}, B_{12}, C_{12}, D_{12}) \end{bmatrix} \quad (2)$$

$$Input_3 = \begin{bmatrix} Median(A_1, B_1, C_1, D_1), Median(A_2, B_2, C_2, D_2), \ldots \\ , Median(A_{12}, B_{12}, C_{12}, D_{12}) \end{bmatrix} \quad (3)$$

$$Input_{4,\text{and } 5} = [((A_1 \times W_1) + (B_1 \times W_2) + (C_1 \times W_3) + (D_1 \times W_4)), ((A_2 \times W_1) + (B_2 \times W_2) + (C_2 \times W_3) + (D_2 \times W_4)), \ldots, ((A_{12} \times W_1) + (B_{12} \times W_2) + (C_{12} \times W_3) + (D_{12} \times W_4))] \quad (4)$$

We note that, for $Input_4$ and $Input_5$, the monthly data of the years 2011, 2012, 2013, and 2014 are multiplied by the weighting factors. W_1, W_2, W_3, and W_4 are the weighting factors, where 0 < weighting factor < 1, $W_1 < W_2 < W_3 < W_4$, and $W_1 + W_2 + W_3 + W_4 = 1$. For $Input_4$, W_1, W_2, W_3, and W_4 are set to 0.1, 0.2, 0.3, and 0.4, respectively (i.e. linear weighting value). For $Input_5$, W_1, W_2, W_3, and W_4 are set to 0.078125, 0.140625, 0.265625, and 0.515625, respectively (i.e. exponential weighting value). By our setting, the weighting factor with the high value is applied to the input data of the recent year. This will give high priority to recent input data. Five designed input data are shown in Table 3.

Table 3 Designed input data for the first case

Months	Designed input data for the first case				
	$Input_1$	$Input_2$	$Input_3$	$Input_4$	$Input_5$
1	236.13	202.18	235.90	225.36	227.25
2	337.14	284.20	328.57	315.79	319.42
3	505.00	458.83	503.95	496.93	500.39
4	745.00	541.96	619.00	631.75	657.26
5	622.41	417.68	439.32	495.88	525.52
6	373.33	244.33	227.34	283.37	303.31
7	187.10	178.87	175.17	194.32	195.13
8	211.29	220.32	239.52	240.16	236.03
9	289.33	242.25	292.17	273.19	276.97
10	370.97	238.86	222.24	274.83	294.16
11	326.33	215.58	198.00	243.33	259.39
12	222.58	195.86	195.92	199.41	203.08

In the second case, five designed input data are also assigned; $Input_1$ to $Input_5$ as shown in (5) to (8), respectively. For $Input_4$ and $Input_5$, the monthly data of the years 2011, 2012, 2013, 2014, and 2015 are multiplied by the weighting factors (i.e. W_1, W_2, W_3, W_4 and W_5), where 0 < weighting factor < 1, $W_1 < W_2 < W_3 < W_4 < W_5$, and $W_1 + W_2 + W_3 + W_4 + W_5 = 1$. For $Input_4$, W_1, W_2, W_3, W_4, and W_5 are set to 0.06667, 0.13333, 0.2, 0.26667 and 0.33333, respectively (i.e. linear weighting value). For $Input_5$, W_1, W_2, W_3, W_4 and W_5 are set to 0.0375, 0.06875, 0.13125, 0.25625 and 0.50625, respectively (i.e. exponential weighting value). Five designed input data for this case are also shown in Table 4.

$$Input_1 = [E_1, E_2, \ldots, E_{12}] \quad (5)$$

$$Input_2 = \begin{bmatrix} Mean(A_1, B_1, C_1, D_1, E_1), Mean(A_2, B_2, C_2, D_2, E_2), \ldots \\ , Mean(A_{12}, B_{12}, C_{12}, D_{12}, E_{12}) \end{bmatrix} \quad (6)$$

$$Input_3 = \begin{bmatrix} Median(A_1, B_1, C_1, D_1, E_1), Median(A_2, B_2, C_2, D_2, E_2), \ldots \\ , Median(A_{12}, B_{12}, C_{12}, D_{12}, E_{12}) \end{bmatrix} \quad (7)$$

$$Input_{4,\text{and } 5} = [((A_1 \times W_1) + (B_1 \times W_2) + (C_1 \times W_3) + (D_1 \times W_4) + (E_1 \times W_5)), ((A_2 \times W_1) + (B_2 \times W_2) + (C_2 \times W_3) + (D_2 \times W_4) + (E_2 \times W_5)), \ldots, ((A_{12} \times W_1) + (B_{12} \times W_2) + (C_{12} \times W_3) + (D_{12} \times W_4) + (E_{12} \times W_5))] \quad (8)$$

Table 4 Designed input data for the second case

Months	Designed input data for the second case				
	$Input_1$	$Input_2$	$Input_3$	$Input_4$	$Input_5$
1	261.94	214.13	236.13	237.55	244.97
2	314.29	290.22	320.00	315.29	317.04
3	398.21	446.70	502.90	464.03	448.92
4	544.83	542.53	561.33	602.77	601.06
5	581.10	450.37	542.19	524.29	554.33
6	298.33	255.13	281.67	288.35	301.16
7	200.00	183.09	187.10	196.22	197.69
8	182.26	212.71	211.29	220.86	208.91
9	200.00	233.80	289.33	248.79	238.22
10	232.26	237.54	232.26	260.64	263.17
11	218.33	216.13	200.00	234.99	238.88
12	200.00	196.69	200.00	199.61	201.57

2.3 The EWMA Method

As mentioned before, the EWMA method is used to forecast monthly lime prices. The forecasted output after applying the EWMA method is shown in (9), where Y_i is the forecasted value at the sample number i (i.e. month), X_i is the input value as shown in Table 3 and 4, Y_{i-1} is the forecasted value at the sample number $i-1$ (i.e. latest month), and α is the weighting factor. By (9), the forecasted output directly depends on the previous forecasted value and the recent input value multiplied by the weighting factor $(0 \leq \alpha \leq 1)$. α close to 1 gives high priority to recent changes in the input value, while α close to 0 indicates that the previous forecasted output plays a role in the calculation. In this work, α is varied in the tests to see their response and to find an optimal value. It is varied in nine levels: 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, and 0.9, respectively. Forecasting by the EWMA method is also illustrated in Table 5.

$$Y_i = \alpha \times X_i + (1 - \alpha) \times Y_{i-1} \quad (9)$$

We note that the derivation of (9) is shown below. By substituting Y_{i-1}, Y_{i-2},... Y_1 into (9), the general form of the EWMA can be written by (10). The weighting for each older datum decreases exponentially.

$$Y_i = \alpha \times X_i + (1-\alpha) \times [\alpha \times X_{i-1} + (1-\alpha) \times Y_{i-2}]$$
$$= \alpha \times X_i + \alpha \times (1-\alpha) \times X_{i-1} + (1-\alpha)^2 \times Y_{i-2}$$
$$= \alpha \times X_i + \alpha \times (1-\alpha) \times X_{i-1} + (1-\alpha)^2 \times [\alpha \times X_{i-2} + (1-\alpha) \times Y_{i-3}]$$
$$= \alpha \times X_i + \alpha \times (1-\alpha) \times X_{i-1} + \alpha \times (1-\alpha)^2 \times X_{i-2} + (1-\alpha)^3 \times Y_{i-3}$$
.
.
.
$$Y_i = \alpha \times X_i + \alpha \times (1-\alpha) \times X_{i-1} + \alpha \times (1-\alpha)^2 \times X_{i-2} + \cdots + \alpha \times (1-\alpha)^{i-1} \times Y_1, \text{ where } Y_1 = X_1 \quad (10)$$

Table 5 Forecasting by the EWMA method

Forecasting by the EWMA method		
Months	***Input***	**Forecasted results**
1	X_1	$Y_1 = X_1$
2	X_2	$Y_2 = \alpha \times X_2 + (1-\alpha) \times Y_1$
3	X_3	$Y_3 = \alpha \times X_3 + (1-\alpha) \times Y_2$
4	X_4	$Y_4 = \alpha \times X_4 + (1-\alpha) \times Y_3$
5	X_5	$Y_5 = \alpha \times X_5 + (1-\alpha) \times Y_4$
6	X_6	$Y_6 = \alpha \times X_6 + (1-\alpha) \times Y_5$
7	X_7	$Y_7 = \alpha \times X_7 + (1-\alpha) \times Y_6$
8	X_8	$Y_8 = \alpha \times X_8 + (1-\alpha) \times Y_7$
9	X_9	$Y_9 = \alpha \times X_9 + (1-\alpha) \times Y_8$
10	X_{10}	$Y_{10} = \alpha \times X_{10} + (1-\alpha) \times Y_9$
11	X_{11}	$Y_{11} = \alpha \times X_{11} + (1-\alpha) \times Y_{10}$
12	X_{12}	$Y_{12} = \alpha \times X_{12} + (1-\alpha) \times Y_{11}$

According to (10), an example of the forecasted result of the month 12 is: $Y_{12} = \alpha \times X_{12} + \alpha \times (1-\alpha) \times X_{11} + \alpha \times (1-\alpha)^2 \times X_{10} + \cdots + \alpha \times (1-\alpha)^{11} \times X_1$

2.4 The DEWMA, the MHW and the AHW Methods

To evaluate the performance of the proposed method, we also compare our proposed method with the DEWMA, the MHW, and the AHW methods. They are introduced in details below. We note that the input (i.e. X_i) inserted for these three methods is the raw data (i.e. the lime prices from January 2011 to September 2016), as shown in Table 1.

For the DEWMA method, also known as Holt's Linear Exponential method, it is appropriately used when the data shows the trend [4-6]. It adds a trend factor to the equation as a way of adjusting for the trend. There are three equations incorporated in this method as shown in (11) to (13). Where L_i is an estimate of the level of the data series at the sample number i, b_i is an estimate of the trend of the data series at the sample number i, α and β are the weighting factors (with values between 0 and 1), Y_{i+m} is the forecasted value for the period $i+m$ (i.e. $m > 0$), and m is the number of forecast periods ahead. As suggested by [4, 5, 7], to set the initial values for L_i and b_i, we set $L_1 = X_1$ and $b_i = 0$. Note that, L_i and b_i can be set by other options as recommended by [4, 5, 7]. However, we test and select the one that gives the minimum of forecasting error. In addition, during our test, optimal values of α and β are also determined; they are selected when the forecasting error is minimized [4, 7, 8, 12].

$$L_i = \alpha \times X_i + (1-\alpha) \times (L_{i-1} + b_{i-1}) \quad (11)$$

$$b_i = \beta \times (L_i - L_{i-1}) + (1-\beta) \times b_{i-1} \quad (12)$$

$$Y_{i+m} = L_i + (m \times b_i) \quad (13)$$

When the data series have the seasonality pattern, both the EWMA and the DEWMA methods cannot perform well. The Triple exponentially weighted moving average method, also known as Holt-Winters method is more appropriate [4-6]. The Holt-Winters method is directly used when the trend and the seasonality behaviors are present in the series [6]. It incorporates three equations; first for the level, second for the trend, and third for the seasonality. Generally, there are two Holt-Winters methods depending on whether the seasonality is modelled in a multiplicative form or an additive form. The equations for the MHW method are expressed in (14) to (17) (Note that (15) is identical to (12)). Where S_i is a multiplicative seasonal component, γ is the weighting factor (with values between 0 and 1), and n is the length of the seasonality (i.e. number of months in a year). As suggested by [4-7], to initialize the level, we set $L_n = (X_1 + X_2 + \cdots + X_n)/n$ (i.e. in our case n = 12 months). To initialize the trend, we set $b_n = 0$. Finally, to initialize the seasonal components, we set $S_i = X_i/L_n$, where $i = 1,2,\ldots,12$.

$$L_i = \alpha \times \left(\frac{X_i}{S_{i-m}}\right) + (1-\alpha) \times (L_{i-1} + b_{i-1}) \quad (14)$$

$$b_i = \beta \times (L_i - L_{i-1}) + (1-\beta) \times b_{i-1} \quad (15)$$

$$S_i = \gamma \times \left(\frac{X_i}{L_i}\right) + (1-\gamma) \times S_{i-n} \quad (16)$$

$$Y_{i+m} = \big(L_i + (m \times b_i)\big) \times S_{i-n+m} \quad (17)$$

The equations for the AHW method are expressed in (18) to (21) (Note that (19) is identical to (15) and (12)). The initial values for the level and the trend are identical to those for the MHW method. To initialize the level, we set $S_i = X_i - L_n$, where $i = 1,2,\ldots,12$ [4-6]. For both the MHW and the AHW methods, during our test, optimal values of α, β and γ are automatically determined and selected when the forecasting error is minimized [4, 7, 8, 12].

$$L_i = \alpha \times (X_i - S_{i-m}) + (1-\alpha) \times (L_{i-1} + b_{i-1}) \quad (18)$$

$$b_i = \beta \times (L_i - L_{i-1}) + (1-\beta) \times b_{i-1} \quad (19)$$

$$S_i = \gamma \times (X_i - L_i) + (1-\gamma) \times S_{i-n} \quad (20)$$

$$Y_{i+m} = L_i + (m \times b_i) + S_{i-n+m} \quad (21)$$

2.5 Performance Index

To evaluate the performance of the forecasting methods discussed above, the forecasting error represented by the Mean Absolute Percentage Error (MAPE) [10, 12], which indicates how much the average of absolute error of the forecasted data compared to the actual data, is selected as the performance index. The MAPE is chosen because it provides the accurate and fair comparison of forecasting methods, and it is not prone to change in the magnitude of time series to be forecasted [16, 17]. Also, it frequently used in practice [18]. The MAPE denotes by (22), where N denotes the number of data sample, e_t denotes the forecasting error from $\acute{Y}_t - Y_i$. $\acute{Y}_t$ is the actual data, and Y_i is the forecasted data determined by the forecasting methods with the optimal weighting factors (i.e. α, β and γ). The 95% Confidence Interval (CI) is also provided for average results. We note that in the proposed method, N is 12 months for the first case and 9 months for the second case, and $\acute{Y}_t$ refers to E_1 to E_{12} for the first case and F_1 to F_9 for the second case, as seen in Table 2.

$$MAPE = \frac{\sum_{i=1}^{N} \left|\frac{e_i}{\acute{Y}_i}\right|}{N} \times 100 \tag{22}$$

3.0 RESULTS AND DISCUSSION

In the first case (i.e. forecasting monthly lime prices of the year 2015), the MAPE results by applying the inputs 1 to 5 are shown in Figure 1. The results with and without applying the EWMA method are also compared (i.e. without applying the EWMA method means that the input values are the forecasted values directly). The results indicate that using the EWMA method with the optimal weighting factor gives the MAPE lower than the case without applying the EWMA method. Additionally, using the input 2 (i.e. the average monthly data of the year 2011 to 2014) as the input data provides the lowest MAPE (i.e. MAPE = 9.93). Note that the forecasted data by using the input 2 are also illustrated in Table 6. In this case, the input 2 provides the better result than the input 3 (i.e. the median of the monthly data of the year 2011 to 2014), the input 4 (i.e. the monthly data of the year 2011 to 2014 after applying the linear weighting factor), the input 5 (i.e. the average monthly data of the year 2011 to 2014 after applying the exponential weighting factor), and the input 1 (i.e. the monthly data of the year 2014), respectively. For the optimal weighting factors (i.e. λ) which give the minimum value of the MAPE for the inputs 1 to 5, they are equal to 0.9, 0.8, 0.7, 0.9, and 0.9, respectively, as shown in Figure 2.

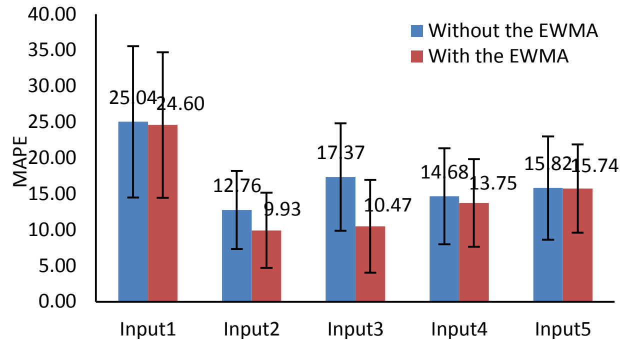


Figure 1 The MAPE by applying the inputs 1 to 5 (in the first case)

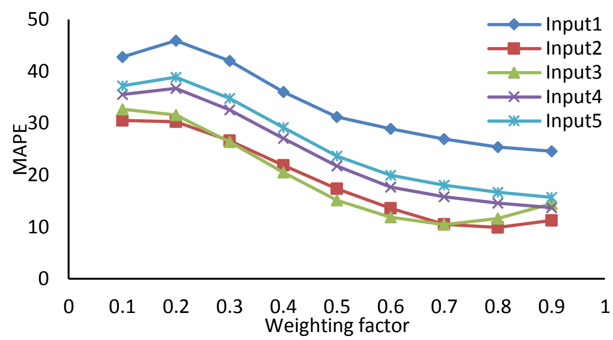


Figure 2 The weighting factor versus the MAPE in the case of using the inputs 1 to 5 (in the first case)

Table 6 The comparison of monthly lime prices of the year 2015 between the raw data and the forecasted data determined by the EWMA method with the optimal weighting factor and using the input 2

Monthly lime prices of the years 2015		
Months	**Raw data**	**Forecasted data**
1	261.94	202.18
2	314.29	267.79
3	398.21	420.62
4	544.83	517.69
5	581.10	437.68
6	298.33	283.00
7	200.00	199.70
8	182.26	216.19
9	200.00	237.04
10	232.26	238.49
11	218.33	220.17
12	200.00	200.72

In the second case (i.e. forecasting monthly lime price of the year 2016), the MAPE results by applying the inputs 1 to 5 are shown in Figure 3. Like the first case, the results confirm that using the EWMA method significantly gives the MAPE lower than the case without applying the EWMA method, and using the input 2 for the EWMA method provides the lowest MAPE (i.e. MAPE = 13.69). The forecasted data using the input 2 are also shown in Table 7. The forecasted lime prices of October 2016 to December 2016 are also provided; they are 237.23, 226.68 and 211.68 Thai Baht, respectively. In the second case, the optimal weighting factors for the inputs 1 to 5 are 0.5, 0.5, 0.5, 0.4, and 0.4, respectively. They are illustrated in Figure 4.

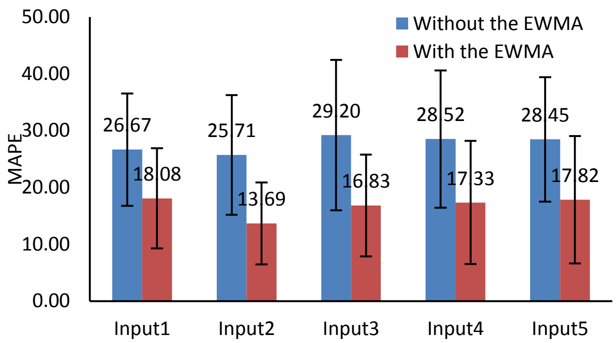


Figure 3 The MAPE by applying the inputs 1 to 5 (in the second case)

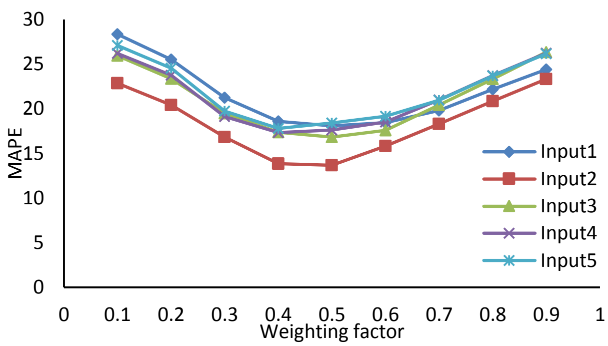


Figure 4 The weighting factor versus the MAPE in the case of using the inputs 1 to 5 (in the second case)

Table 7 The comparison of monthly lime prices of the year 2016 between the raw data and the forecasted data determined by the EWMA method with the optimal weighting factor and using the input 2

Monthly lime prices of the years 2016		
Months	Raw data	Forecasted data
1	210.00	214.13
2	200.00	252.18
3	320.00	349.44
4	421.67	445.98
5	500.00	448.18
6	473.33	351.65
7	264.52	267.37
8	183.87	240.04
9	270.59	236.92
10	-	237.23
11	-	226.68
12	-	211.68

The comparison of the lime price in Thai baht unit between the raw data (as shown in Table 1) and the forecasted data determined by the EWMA method with the optimal weighting factors using the input 2 (as shown in Tables 6 and 7) is illustrated again in Figure 5. This result guarantees that the proposed method presented in Sections 2.2-2.3 can be appropriately applied to forecast monthly lime prices of the years 2015 and 2016 as confirmed by the MAPE results in Figures 1 and 3, although the raw data to be forecasted shows the seasonality. We note that the result in Figure 5 also reveals that the trend of the lime prices seems to be increased during 2011 to 2014 (i.e. the months 1-48) and then decreases during 2014 to 2016. Here, there is more possibility that the lime pieces of the year 2017 may not be different from the year 2016.

The forecasted data determined by the DEWMA, the MHW, and the AHW methods are also demonstrated in Figures 6, 7, and 8, respectively, where the MAPE results with 95% CI and the optimal weighting factors which give the minimum of the MAPE are listed in Table 8. The result shows that among these three methods, the AHW method provides better performance than the MHW method and the DEWMA method.

Table 8 The MAPE and the optimal weighting factors by the DEWMA, the MHW, and the AHW methods

Methods	MAPE	95% CI	Optimal weighting factors		
			α	β	γ
DEWMA	28.57	6.41	1.000	0.000	-
MHW	24.72	4.88	0.043	0.000	0.549
AHW	23.83	4.84	0.045	≈ 0.000	0.626

Note that the MAPE by these three methods is calculated from the forecasted data of the months 13 to 69 (i.e. January 2012 to September 2016)

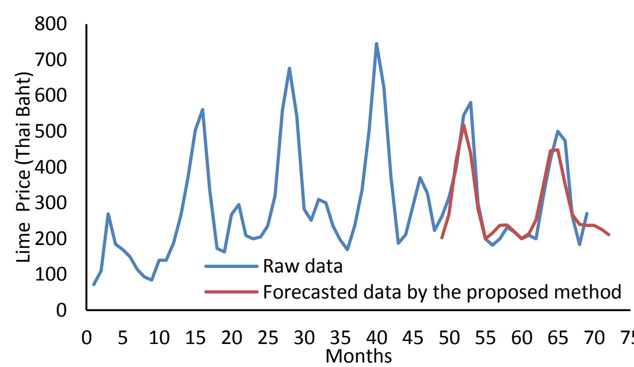


Figure 5 The comparison of the lime prices between the raw data and the forecasted data determined by the EWMA method with the optimal weighting factor and using the input 2 (as shown in Tables 6 and 7)

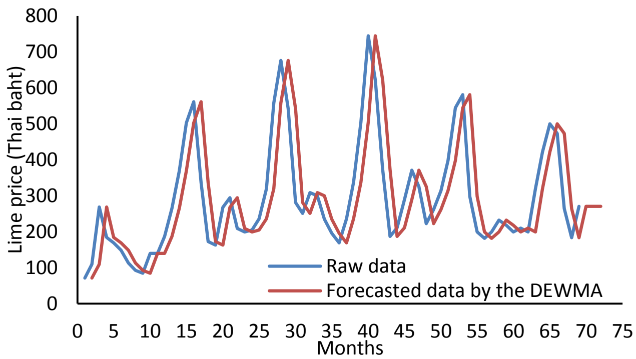


Figure 6 The comparison of the lime prices between the raw data and the forecasted data determined by the DEWMA method with the optimal weighting factors; the forecasted lime prices of October 2016 to December 2016 are 270.59, 270.59 and 270.59 Thai Baht, respectively

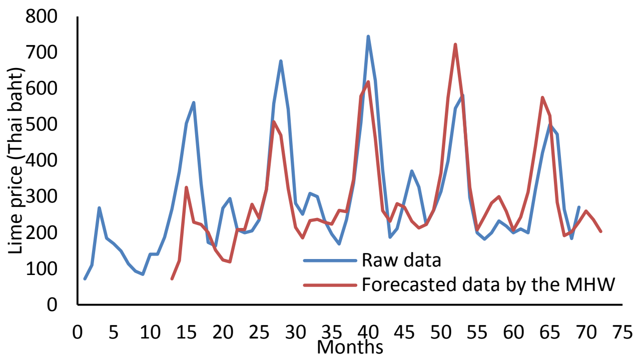


Figure 7 The comparison of the lime prices between the raw data and the forecasted data determined by the MHW method with the optimal weighting factors; the forecasted lime prices of October 2016 to December 2016 are 259.75, 236.16 and 203.19 Thai Baht, respectively

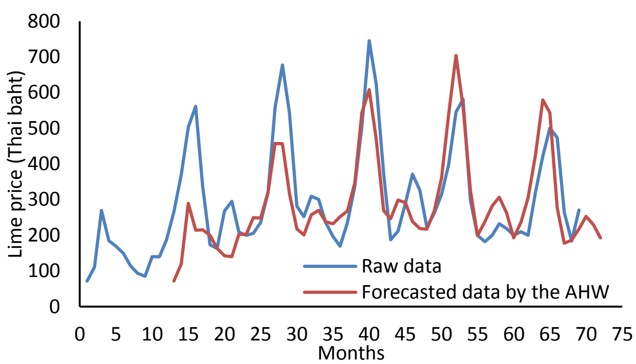


Figure 8 The comparison of the lime prices between the raw data and the forecasted data determined by the AHW method with the optimal weighting factors; the forecasted lime prices of October 2016 to December 2016 are 252.42, 229.75 and 192.84 Thai Baht, respectively

Finally, figure 9 shows the comparison of the MAPE results determined by the proposed method using the input 2 (i.e. method 1), the DEWMA method (i.e. method 2), the MHW method (i.e. method 3), and the AHW method (i.e. method 4), where the MAPE is calculated from the forecasted data of the months 49 to 69 (i.e. during January 2015 to September 2016). This result confirms that the proposed method can be properly used to forecast monthly lime prices in Thailand compared with the methods (i.e. the MHW and the AHW methods) which are directly designed by taking the seasonality into considerations.

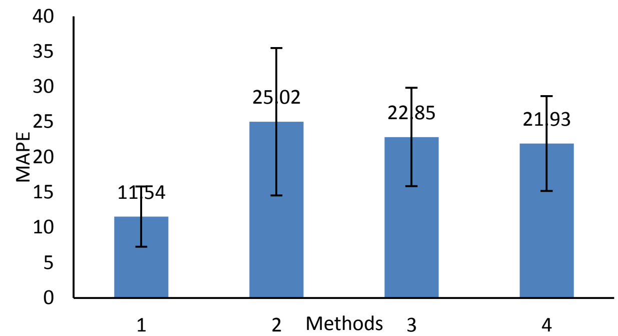


Figure 9 The comparison of the MAPE determined by the proposed method using the input 2 (i.e. method 1), the DEWMA method (i.e. method 2), the MHW method (i.e. method 3), and the AHW method (i.e. method 4)

4.0 CONCLUSION

In this paper, the EWMA method is used to forecast monthly lime prices and five different input data are defined and assigned for the EWMA method. We show that although the EWMA method is not suitable for forecasting data which present trend and seasonality behaviors and it is used only for short-range forecasting, the proposed method can handle such mentioned problems. Our study reveals that using the average monthly data as the input data for the EWMA method with an optimal weighting factor setting to forecast monthly lime prices shows better results as confirmed by the MAPE. The proposed method also performs well compared with the DEWMA, the MHW, and the AHW methods. We believe that our research methodology proposed in this work can be applied to forecast monthly lime prices for the next year. Also, our results are useful for Thai agriculturists to plan their works and sales.

To apply the proposed method with other datasets, we have some recommendations. Firstly, since the designed input data for the EWMA method (i.e. the inputs 1 to 5) are calculated from the data of the past years (i.e. dataset), the forecasting accuracy directly depends on numbers of dataset. Using the small numbers of dataset to determine the designed input data may lead to high forecasting error. Secondly, among five designed inputs, which input gives better performance should be determined when the proposed method is applied to forecast other datasets. This is because the different datasets have the different characteristics and behaviors.

Acknowledgement

This research was supported by the Faculty of Management Sciences, Nakhon Si Thammarat Rajabhat University, Thailand, and the Faculty of Engineering, Thaksin University, Phatthalung Campus, Thailand.

References

[1] Brown, R.G. 1956. Exponential Smoothing for Predicting Demand. *10th National Meeting of the Operations Research Society of America, San Francisco*.

[2] Hunter, J. H. 1986. The Exponentially Weighted Moving Average. *Journal of Quality Technology*. 18(4): 203-210.

[3] Winters, P. 1960. Forecasting Sales by Exponentially Weighted Moving Averages. *Management Science*. 6: 324-342.

[4] Montgomery, D. C., Jennings, C. L., and Kulahci, M. 2008. Introduction to Time Series Analysis and Forecasting. *Wiley Series in Probability and Statistics.* John Wiley and Sons, Hoboken, New Jersey, USA.

[5] Kalekar, P. S. 2004. Time Series Forecasting Using Holt-Winters Exponential Smoothing. Kanwal Rekhi School of Information Technology.

[6] Holt, C. C. 2004. Forecasting Seasonals and Trends by Exponentially Weighted Moving Averages. *International Journal of Forecasting*. 20(1): 5-10.

[7] Dhakre, D. S., Sarkar, K. A., and Manna, S. 2016. Forecasting Price of Brinjal by Holt Winters Method in West Bengal Using MS Excel. *International Journal of Bio-resource, Environment and Agricultural Sciences*. 2(1): 232-235.

[8] Gardner, E. S. 1985. Exponential Smoothing: The State of the Art. *Journal of Forecasting*. 4: 1-28.

[9] De Gooijer, J. G., and Hyndman, R. J. 2006. 25 Years of Time Series Forecasting. *International Journal of Forecast*. 22(3): 443–473.

[10] Chatfield, C. 2001. *Time-Series Forecasting.* Chapman & Hall, New York.

[11] Simummuang Market, Retrieved June 2017 from http://www.taladsimummuang.com/dmma/Portals/PriceList.aspx.

[12] Tratar, L. F., and Srmcnik, E. 2016. The Comparison of Holt-Winters Method and Multiple Regression Methods: A Case Study. *Energy*. 109(2016): 266-276.

[13] Tratar, L. F., Mojskerc, B., and Toman, A. 2016. Demand Forecasting with Four-Parameter Exponential Smoothing. *International Journal of Production Economics*. 181(2016): 162-173.

[14] Ramos, P., Santos, N., and Rebelo, R. 2015. Performance of State Space and ARIMA models for Consumer Retail Sales Forecasting. *Robotics and Computer-Integrated Manufacturing*. 34(2015): 151-163.

[15] Tratar, L. F. 2016. Forecasting Method for Noisy Demand. *International Journal of Production Economics*. 161(2015): 64-73.

[16] Gentry, T. W., Wiliamowski, B. M., and Weatherford, L. R. 1995. A Comparison of Traditional Forecasting Techniques and Neural Networks. *Intelligent Engineering Systems through Artificial Neural Networks*. 5: 765-770.

[17] Alon, I., Qi, M., and Sadowski, R. J. 2001. Forecasting Aggregate Retail Sales: A Comparison of Artificial Neural Networks and Traditional Methods. *Journal of Retailing and Consumer Services.* 8(3): 147-156.

[18] Ravindran, A., and Warsing, D.P. 2013. *Supply Chain Engineering: Models and Applications.* New York. NY: CRC Press.